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# L1-Norm Regularized Deconvolution of Functional MRI BOLD Signal

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**Abstract -** Deconvolution methods are used to denoise the blood oxygen level-dependent (BOLD) response, the signal that forms the basis of functional MRI (fMRI). In this work we propose a novel approach based on a temporal regularized deconvolution of the BOLD fMRI signal with the least absolute shrinkage and selection operator (LASSO) model, solved using the angle regression algorithm (LARS). In this way we were able to recover the underlying neurons activations and their dynamics.

## 1 Introduction

**Problem**

**Recover brain activations** and their dynamics without a-priori hypotheses.

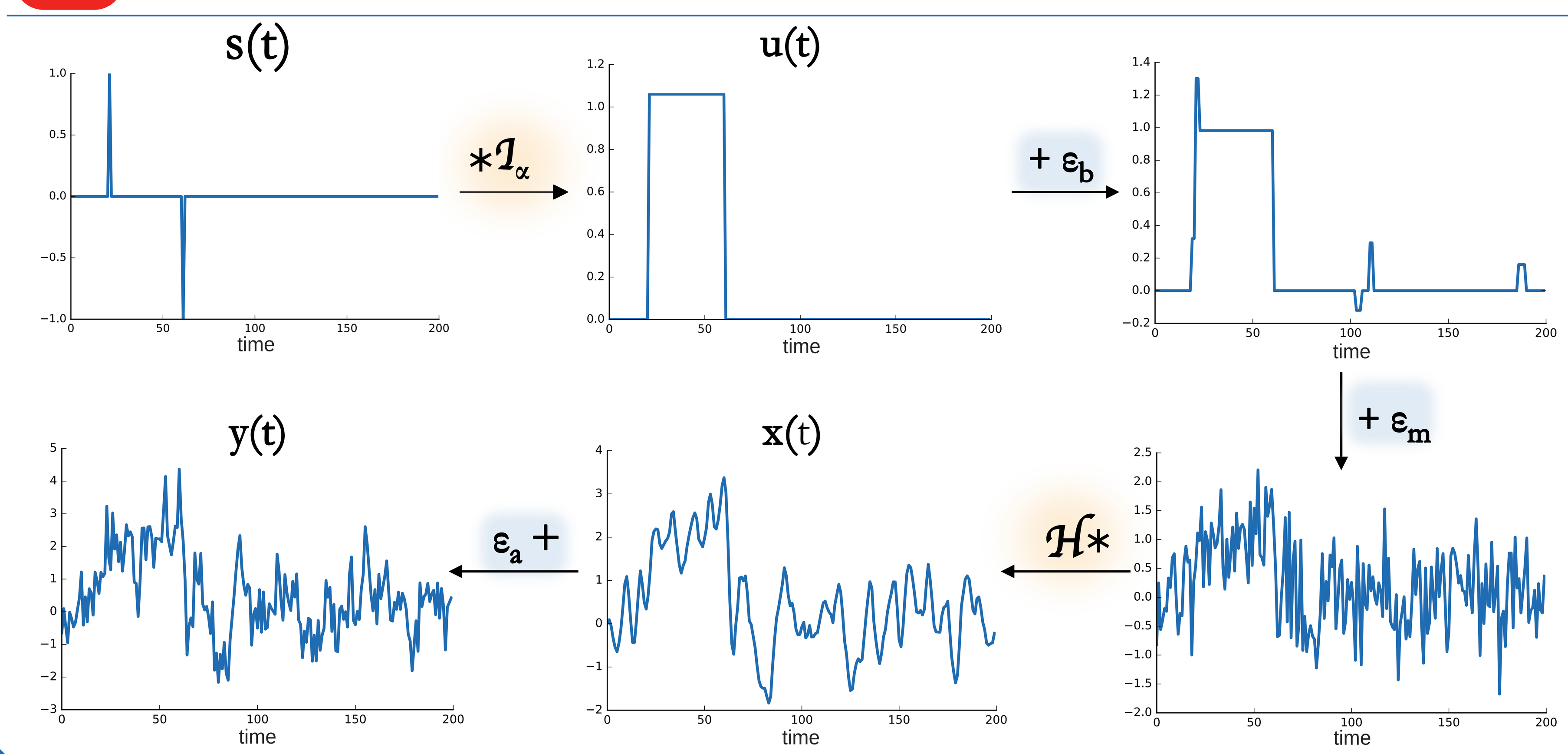
**Goal**

**Denoise** the blood oxygen level dependent (**BOLD**) functional MRI (fMRI) **response**.

**Our method**

**Temporal regularized deconvolution** of the BOLD signal with the least absolute shrinkage and selection operator (**LASSO**) model, solved using the Least-Angle Regression (**LARS**) algorithm.

## 2 Model of the BOLD fMRI signal




s(t): innovation signal
u(t): activity-inducing signal
x(t): activity-related signal

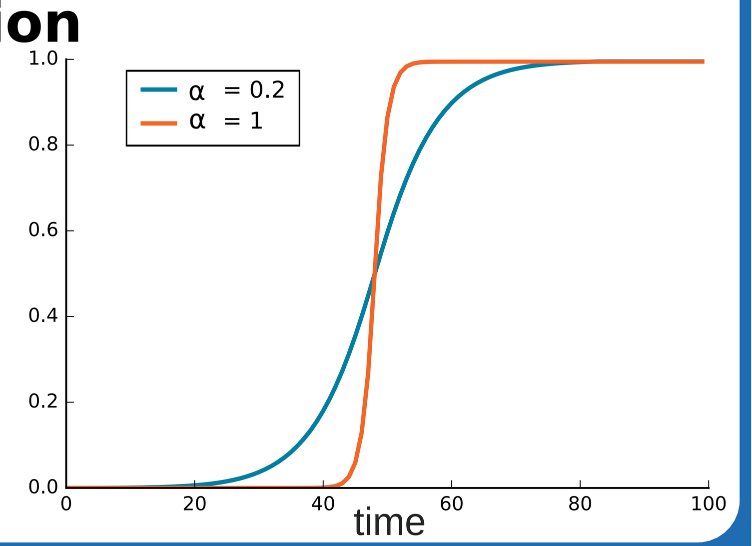
$\varepsilon_b$: block-type noise
$\varepsilon_m$: model random gaussian noise
$\varepsilon_a$: additive random gaussian noise

- $\mathcal{H}$: BOLD response
- **$\mathcal{I}_\alpha$: Exponential accumulation function**

$$\mathcal{I}_\alpha(z) = S\left[\frac{e^{-\alpha}z^{-1}}{(1-e^{-\alpha}z^{-1})^2} - \frac{e^{-\alpha}z}{(1-e^{-\alpha}z)^2}\right]\frac{1}{(1-z^{-1})^2}$$

S: normalization term

$\alpha \subset [0, 3]$




## 3 Regularization

We exploited the sparsity of the signal s(t) such that:

$$s* = \underset{s}{\operatorname{argmin}}\left\{\frac{1}{2n}||\mathbf{y} - \mathcal{A}\mathbf{s}||_2^2 + \lambda||\mathbf{s}||_1\right\}$$

$\mathcal{A}s = \mathcal{H} * \mathcal{I}_\alpha * \mathrm{s}(t)$; λ: regularization parameter; n: signal length.

## 4 Solution of the inverse problem

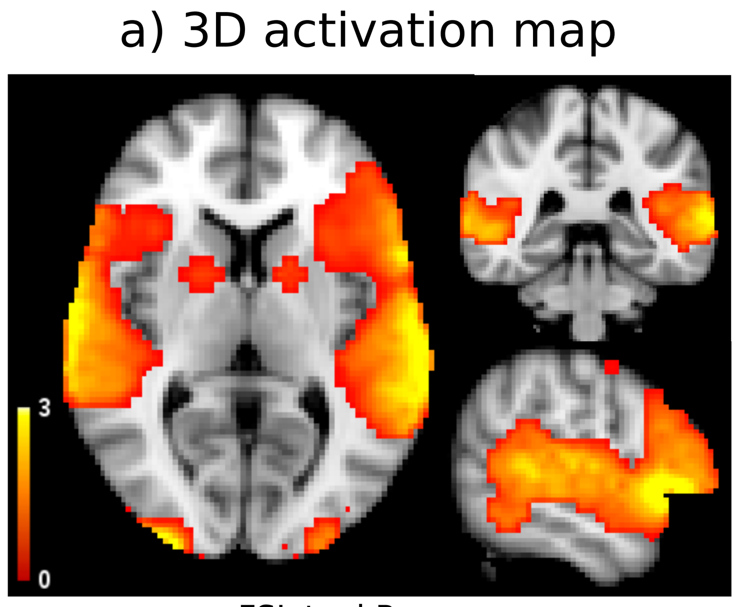
1 LARS → All λ and their associated solutions s* at once.

2 L-Curve → Optimal λ* and its associated solution s*.

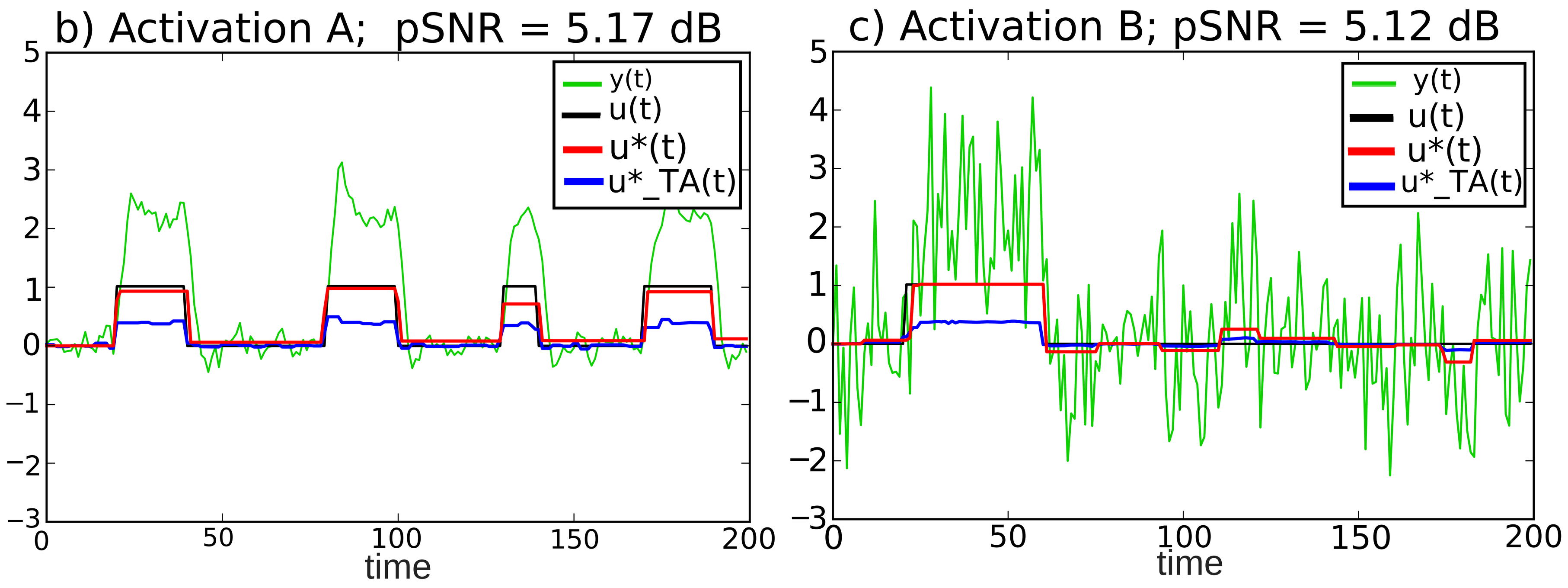
## 5 Simulations and Validation

### SIMULATED DATA

a) 3D activation map



FSL tool Possum



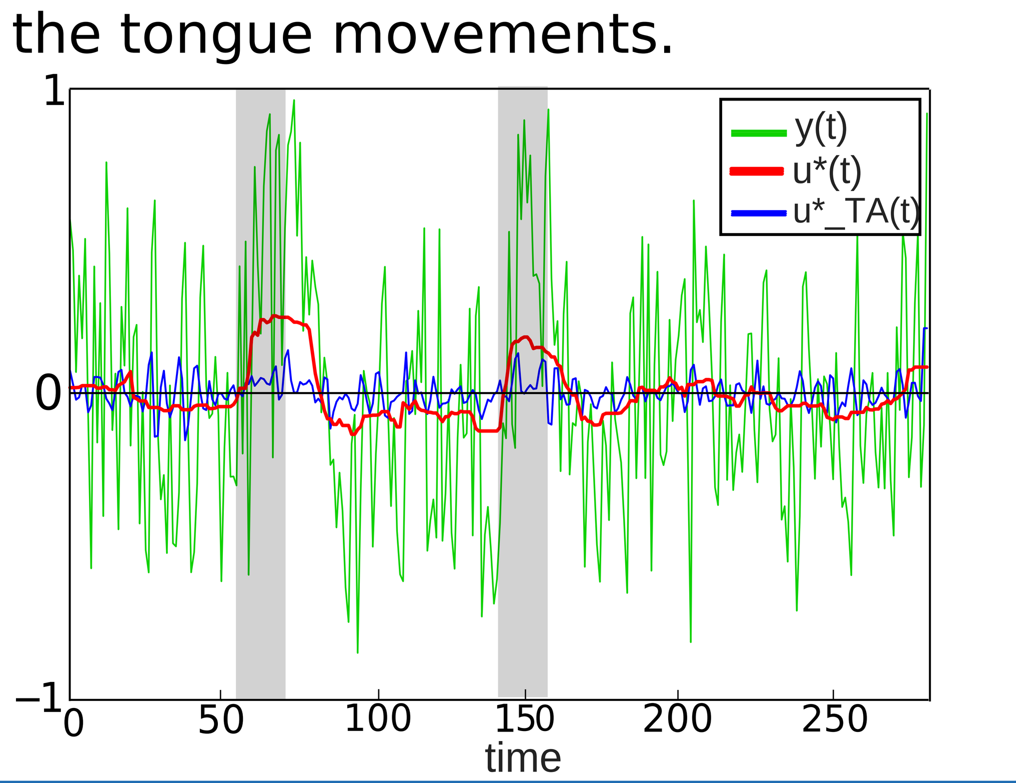

**a)** The fMRI signals y(t) were simulated on a 3D activation map.
**b, c)** The reconstructed signals u*(t) obtained with our approach (red) and the Total Activation tool[2] (TA, blue) are superimposed on the activation (black) and fMRI signal (green). Only the gray matter (GM) voxels were considered for analyses.

Summary of rooted MSEs and STDs.

| Activation | | A | | | | | B | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| pSNR [dB] | | 3.14 | 4.96 | 5.17 | 4 | 3.98 | 3.29 | 6.84 | 7.64 | 5.94 | 5.12 |
| OUR α = 0.75 | rMSE | 0.34 | 0.15 | **0.11** | 0.22 | 0.18 | 0.31 | **0.1** | **0.05** | 0.19 | **0.14** |
| | rSTD | 0.2 | 0.14 | **0.13** | 0.16 | 0.14 | 0.17 | **0.07** | **0.05** | 0.11 | **0.08** |
| TA | rMSE | 0.36 | 0.26 | 0.24 | 0.29 | 0.3 | 0.32 | 0.2 | 0.19 | 0.24 | 0.25 |
| | rSTD | 0.33 | 0.31 | 0.31 | 0.32 | 0.33 | 0.27 | 0.23 | 0.23 | 0.24 | 0.26 |

### REAL fMRI DATA

- Preprocessed HCP motor **task-fMRI data**.
- The reconstructed u*(t) were averaged in a 6×6×6 $mm^3$ ROI centered in BA4p.
- The gray areas represents the duration of the tongue movements.




## 6 Conclusion

- The **joint** use of the **LARS** algorithm and the **L-curve** allowed us to choose the optimal **solution** among all those **outputted at once**.
- We **decreased** the **computation time** and **avoided** a need of defining **λ a priori**.
- We improved brain dynamics recovery for future clinical applications.
- Future works will involve also a spatial regularization.

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**References -** **[1]** Y. Farouj, Regularized spatiotemporal deconvolution of fMRI data using gray-matter constrained total variation. ISBI 2017. **[2]** F.I. Karahanolu, Total activation: fMRI deconvolution through spatio-temporal regularization. Neuroimage, 2013. **[3]** I. Khalidov, Activelets: Wavelets for sparse representation of hemodynamic responses. Signal Processing, 2011. **[4]** B. Efron, Least angle regression. The Annals of statistics, 2004. **[5]** D.C. Van Essen, The Wu-Minn HCP. Neuroimage, 2013. **[6]** V. Kiviniemi, ICAponent analysis of nondeterministic fmri signal sources, Neuroimage, 2003.

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